autogluon_each_location

October 6, 2023

[1]:
```python
import pandas as pd
import numpy as np



import warnings
warnings.filterwarnings("ignore")

def fix_datetime(X, name):
    # Convert 'date_forecast' to datetime format and replace original column␣
 ↪with 'ds'
    X['ds'] = pd.to_datetime(X['date_forecast'])
    X.drop(columns=['date_forecast'], inplace=True, errors='ignore')
    X.sort_values(by='ds', inplace=True)
    X.set_index('ds', inplace=True)

    # Drop rows where the minute part of the time is not 0
    X = X[X.index.minute == 0]
    return X



def convert_to_datetime(X_train_observed, X_train_estimated, X_test, y_train):
    X_train_observed = fix_datetime(X_train_observed, "X_train_observed")
    X_train_estimated = fix_datetime(X_train_estimated, "X_train_estimated")
    X_test = fix_datetime(X_test, "X_test")


    X_train_observed["estimated_diff_hours"] = 0
    X_train_estimated["estimated_diff_hours"] = (X_train_estimated.index - pd.
 ↪to_datetime(X_train_estimated["date_calc"])).dt.total_seconds() / 3600
    X_test["estimated_diff_hours"] = (X_test.index - pd.
 ↪to_datetime(X_test["date_calc"])).dt.total_seconds() / 3600

    X_train_estimated["estimated_diff_hours"] =␣
 ↪X_train_estimated["estimated_diff_hours"].astype('int64')
    # the filled once will get dropped later anyways, when we drop y nans
```

```
    X_test["estimated_diff_hours"] = X_test["estimated_diff_hours"].fillna(-50).
 ↪astype('int64')


    X_train_estimated.drop(columns=['date_calc'], inplace=True)
    X_test.drop(columns=['date_calc'], inplace=True)

    y_train['ds'] = pd.to_datetime(y_train['time'])
    y_train.drop(columns=['time'], inplace=True)
    y_train.sort_values(by='ds', inplace=True)
    y_train.set_index('ds', inplace=True)

    return X_train_observed, X_train_estimated, X_test, y_train




def preprocess_data(X_train_observed, X_train_estimated, X_test, y_train,␣
 ↪location):
    # convert to datetime
    X_train_observed, X_train_estimated, X_test, y_train =␣
 ↪convert_to_datetime(X_train_observed, X_train_estimated, X_test, y_train)

    y_train["y"] = y_train["pv_measurement"].astype('float64')
    y_train.drop(columns=['pv_measurement'], inplace=True)
    X_train = pd.concat([X_train_observed, X_train_estimated])


    # clip all y values to 0 if negative
    y_train["y"] = y_train["y"].clip(lower=0)

    X_train = pd.merge(X_train, y_train, how="outer", left_index=True,␣
 ↪right_index=True)

    X_train["location"] = location
    X_test["location"] = location

    return X_train, X_test
# Define locations
locations = ['A', 'B', 'C']

X_trains = []
X_tests = []
# Loop through locations
for loc in locations:
    print(f"Processing location {loc}...")
    # Read target training data
```

```
    y_train = pd.read_parquet(f'{loc}/train_targets.parquet')

    # Read estimated training data and add location feature
    X_train_estimated = pd.read_parquet(f'{loc}/X_train_estimated.parquet')

    # Read observed training data and add location feature
    X_train_observed= pd.read_parquet(f'{loc}/X_train_observed.parquet')

    # Read estimated test data and add location feature
    X_test_estimated = pd.read_parquet(f'{loc}/X_test_estimated.parquet')

    # Preprocess data
    X_train, X_test = preprocess_data(X_train_observed, X_train_estimated,␣
↪X_test_estimated, y_train, loc)

    X_trains.append(X_train)
    X_tests.append(X_test)

# Concatenate all data and save to csv
X_train = pd.concat(X_trains)
X_test = pd.concat(X_tests)
```

```
Processing location A…
Processing location B…
Processing location C…
```

1 Feature enginering

[2]:

```
# temporary
X_train["hour"] = X_train.index.hour
X_train["weekday"] = X_train.index.weekday
X_train["month"] = X_train.index.month
X_train["year"] = X_train.index.year

X_test["hour"] = X_test.index.hour
X_test["weekday"] = X_test.index.weekday
X_test["month"] = X_test.index.month
X_test["year"] = X_test.index.year


to_drop = ["snow_drift:idx", "snow_density:kgm3"]

X_train.drop(columns=to_drop, inplace=True)
X_test.drop(columns=to_drop, inplace=True)

X_train.dropna(subset=['y'], inplace=True)
X_train.to_csv('X_train_raw.csv', index=True)
```

```
X_test.to_csv('X_test_raw.csv', index=True)
```

[3]:
```
import autogluon.eda.auto as auto
auto.dataset_overview(train_data=X_train, test_data=X_test, label="y",
    sample=None)
```

train_data dataset summary

```
                            count  unique top   freq          mean  \
absolute_humidity_2m:gm3    92951     165                 6.017608
air_density_2m:kgm3         92951     293                 1.255435
ceiling_height_agl:m        72276   40993              2802.588135
clear_sky_energy_1h:J       92951   48602             515154.09375
clear_sky_rad:W             92951    7815               143.101379
cloud_base_agl:m            84404   34862              1692.934692
dew_or_rime:idx             92951       3                 0.007025
dew_point_2m:K              92951     436               275.237762
diffuse_rad:W               92951    2870                39.495815
diffuse_rad_1h:J            92951   48553             142180.03125
direct_rad:W                92951    5296                50.205021
direct_rad_1h:J             92951   41885              180740.1875
effective_cloud_cover:p     92951    1001                67.013519
elevation:m                 92951       3                11.401738
estimated_diff_hours        92951      26                 3.143516
fresh_snow_12h:cm           92951     125                 0.116175
fresh_snow_1h:cm            92951      39                  0.00963
fresh_snow_24h:cm           92951     161                 0.229894
fresh_snow_3h:cm            92951      70                 0.029001
fresh_snow_6h:cm            92951      96                 0.058069
hour                        93024      24                11.501462
is_day:idx                  92951       2                 0.483341
is_in_shadow:idx            92951       2                 0.565384
location                    93024       3   A  34085
month                       93024      12                 6.290484
msl_pressure:hPa            92951     874              1009.502563
precip_5min:mm              92951      64                 0.005674
precip_type_5min:idx        92951       7                 0.083259
pressure_100m:hPa           92951     888                995.81897
pressure_50m:hPa            92951     897              1001.949646
prob_rime:p                 92951     700                 0.756834
rain_water:kgm2             92951      11                 0.009677
relative_humidity_1000hPa:p 92951     788                73.669556
sfc_pressure:hPa            92951     902              1008.107849
snow_depth:cm               92951     165                 0.193203
snow_melt_10min:mm          92951      19                 0.000275
snow_water:kgm2             92951      42                 0.090324
sun_azimuth:d               92951   69692               182.386337
sun_elevation:d             92951   49376                -1.207574
```

super_cooled_liquid_water:kgm2	92951	15	0.056944
t_1000hPa:K	92951	447	279.431061
total_cloud_cover:p	92951	1001	73.604263
visibility:m	92951	85686	33027.933594
weekday	93024	7	3.00215
wind_speed_10m:ms	92951	119	3.037911
wind_speed_u_10m:ms	92951	188	0.662565
wind_speed_v_10m:ms	92951	167	0.6824
wind_speed_w_1000hPa:ms	92951	3	-0.000016
y	93024	12430	287.019652
year	93024	6	2020.69495

	std	min	25%	\
absolute_humidity_2m:gm3	2.714546	0.5	4.0	
air_density_2m:kgm3	0.036608	1.139	1.23	
ceiling_height_agl:m	2521.408447	27.799999	1037.099976	
clear_sky_energy_1h:J	820525.5	0.0	0.0	
clear_sky_rad:W	228.507324	0.0	0.0	
cloud_base_agl:m	1790.963745	27.4	572.200012	
dew_or_rime:idx	0.246032	-1.0	0.0	
dew_point_2m:K	6.83461	247.300003	270.700012	
diffuse_rad:W	60.647518	0.0	0.0	
diffuse_rad_1h:J	215907.21875	0.0	0.0	
direct_rad:W	112.946068	0.0	0.0	
direct_rad_1h:J	401735.03125	0.0	0.0	
effective_cloud_cover:p	35.044811	0.0	41.299999	
elevation:m	7.877236	6.0	6.0	
estimated_diff_hours	8.935328	0.0	0.0	
fresh_snow_12h:cm	0.780374	0.0	0.0	
fresh_snow_1h:cm	0.112621	0.0	0.0	
fresh_snow_24h:cm	1.218249	0.0	0.0	
fresh_snow_3h:cm	0.28067	0.0	0.0	
fresh_snow_6h:cm	0.481389	0.0	0.0	
hour	6.92022	0.0	6.0	
is_day:idx	0.499725	0.0	0.0	
is_in_shadow:idx	0.495709	0.0	0.0	
location				
month	3.587269	1.0	3.0	
msl_pressure:hPa	13.089046	944.299988	1001.400024	
precip_5min:mm	0.033511	0.0	0.0	
precip_type_5min:idx	0.384904	0.0	0.0	
pressure_100m:hPa	13.008334	929.799988	987.799988	
pressure_50m:hPa	13.067102	935.599976	993.900024	
prob_rime:p	5.434649	0.0	0.0	
rain_water:kgm2	0.042968	0.0	0.0	
relative_humidity_1000hPa:p	14.328553	19.5	64.199997	
sfc_pressure:hPa	13.128181	941.400024	1000.0	
snow_depth:cm	1.254293	0.0	0.0	

snow_melt_10min:mm	0.004312	-0.0	-0.0
snow_water:kgm2	0.250991	0.0	0.0
sun_azimuth:d	102.913605	0.008	92.794006
sun_elevation:d	24.010485	-49.979	-18.511
super_cooled_liquid_water:kgm2	0.111482	0.0	0.0
t_1000hPa:K	6.520342	257.899994	274.899994
total_cloud_cover:p	34.993042	0.0	51.700001
visibility:m	18319.150391	130.600006	15798.950195
weekday	2.000961	0.0	1.0
wind_speed_10m:ms	1.778505	0.0	1.7
wind_speed_u_10m:ms	2.808995	-7.3	-1.4
wind_speed_v_10m:ms	1.896996	-9.3	-0.6
wind_speed_w_1000hPa:ms	0.006502	-0.1	0.0
y	766.407785	-0.0	0.0
year	1.187172	2018.0	2020.0

	50%	75%	max \
absolute_humidity_2m:gm3	5.4	7.8	17.5
air_density_2m:kgm3	1.255	1.279	1.441
ceiling_height_agl:m	1803.25	3814.824951	12431.299805
clear_sky_energy_1h:J	4544.899902	778247.25	3006697.25
clear_sky_rad:W	0.0	220.949997	835.299988
cloud_base_agl:m	1128.550049	2016.699951	11688.900391
dew_or_rime:idx	0.0	0.0	1.0
dew_point_2m:K	275.0	280.5	293.799988
diffuse_rad:W	0.0	66.0	340.100006
diffuse_rad_1h:J	9951.700195	236502.75	1182265.375
direct_rad:W	0.0	29.0	684.299988
direct_rad_1h:J	0.0	113366.25	2445897.0
effective_cloud_cover:p	80.800003	99.300003	100.0
elevation:m	7.0	24.0	24.0
estimated_diff_hours	0.0	0.0	39.0
fresh_snow_12h:cm	0.0	0.0	37.400002
fresh_snow_1h:cm	0.0	0.0	7.1
fresh_snow_24h:cm	0.0	0.0	37.400002
fresh_snow_3h:cm	0.0	0.0	20.6
fresh_snow_6h:cm	0.0	0.0	34.0
hour	12.0	17.0	23.0
is_day:idx	0.0	1.0	1.0
is_in_shadow:idx	1.0	1.0	1.0
location			
month	6.0	10.0	12.0
msl_pressure:hPa	1010.299988	1018.599976	1044.099976
precip_5min:mm	0.0	0.0	1.38
precip_type_5min:idx	0.0	0.0	6.0
pressure_100m:hPa	996.799988	1004.900024	1030.900024
pressure_50m:hPa	1002.900024	1011.099976	1037.300049
prob_rime:p	0.0	0.0	97.199997

rain_water:kgm2	0.0	0.0	1.4
relative_humidity_1000hPa:p	76.0	85.099998	100.0
sfc_pressure:hPa	1009.0	1017.200012	1043.800049
snow_depth:cm	0.0	0.0	18.299999
snow_melt_10min:mm	0.0	-0.0	0.18
snow_water:kgm2	0.0	0.1	6.9
sun_azimuth:d	179.526001	271.503479	359.997009
sun_elevation:d	-0.99	15.538	49.917999
super_cooled_liquid_water:kgm2	0.0	0.1	1.4
t_1000hPa:K	278.700012	283.899994	303.299988
total_cloud_cover:p	94.800003	100.0	100.0
visibility:m	37350.300781	48679.550781	76737.796875
weekday	3.0	5.0	6.0
wind_speed_10m:ms	2.7	4.1	15.2
wind_speed_u_10m:ms	0.3	2.5	12.2
wind_speed_v_10m:ms	0.7	1.9	9.0
wind_speed_w_1000hPa:ms	0.0	0.0	0.1
y	0.0	172.92	5733.42
year	2021.0	2022.0	2023.0

	dtypes	missing_count	missing_ratio	raw_type \
absolute_humidity_2m:gm3	float32	73	0.000785	float
air_density_2m:kgm3	float32	73	0.000785	float
ceiling_height_agl:m	float32	20748	0.223039	float
clear_sky_energy_1h:J	float32	73	0.000785	float
clear_sky_rad:W	float32	73	0.000785	float
cloud_base_agl:m	float32	8620	0.092664	float
dew_or_rime:idx	float32	73	0.000785	float
dew_point_2m:K	float32	73	0.000785	float
diffuse_rad:W	float32	73	0.000785	float
diffuse_rad_1h:J	float32	73	0.000785	float
direct_rad:W	float32	73	0.000785	float
direct_rad_1h:J	float32	73	0.000785	float
effective_cloud_cover:p	float32	73	0.000785	float
elevation:m	float32	73	0.000785	float
estimated_diff_hours	float64	73	0.000785	float
fresh_snow_12h:cm	float32	73	0.000785	float
fresh_snow_1h:cm	float32	73	0.000785	float
fresh_snow_24h:cm	float32	73	0.000785	float
fresh_snow_3h:cm	float32	73	0.000785	float
fresh_snow_6h:cm	float32	73	0.000785	float
hour	int64			int
is_day:idx	float32	73	0.000785	float
is_in_shadow:idx	float32	73	0.000785	float
location	object			object
month	int64			int
msl_pressure:hPa	float32	73	0.000785	float
precip_5min:mm	float32	73	0.000785	float

precip_type_5min:idx	float32	73	0.000785	float
pressure_100m:hPa	float32	73	0.000785	float
pressure_50m:hPa	float32	73	0.000785	float
prob_rime:p	float32	73	0.000785	float
rain_water:kgm2	float32	73	0.000785	float
relative_humidity_1000hPa:p	float32	73	0.000785	float
sfc_pressure:hPa	float32	73	0.000785	float
snow_depth:cm	float32	73	0.000785	float
snow_melt_10min:mm	float32	73	0.000785	float
snow_water:kgm2	float32	73	0.000785	float
sun_azimuth:d	float32	73	0.000785	float
sun_elevation:d	float32	73	0.000785	float
super_cooled_liquid_water:kgm2	float32	73	0.000785	float
t_1000hPa:K	float32	73	0.000785	float
total_cloud_cover:p	float32	73	0.000785	float
visibility:m	float32	73	0.000785	float
weekday	int64			int
wind_speed_10m:ms	float32	73	0.000785	float
wind_speed_u_10m:ms	float32	73	0.000785	float
wind_speed_v_10m:ms	float32	73	0.000785	float
wind_speed_w_1000hPa:ms	float32	73	0.000785	float
y	float64			float
year	int64			int

	variable_type	special_types
absolute_humidity_2m:gm3	numeric	
air_density_2m:kgm3	numeric	
ceiling_height_agl:m	numeric	
clear_sky_energy_1h:J	numeric	
clear_sky_rad:W	numeric	
cloud_base_agl:m	numeric	
dew_or_rime:idx	category	
dew_point_2m:K	numeric	
diffuse_rad:W	numeric	
diffuse_rad_1h:J	numeric	
direct_rad:W	numeric	
direct_rad_1h:J	numeric	
effective_cloud_cover:p	numeric	
elevation:m	category	
estimated_diff_hours	numeric	
fresh_snow_12h:cm	numeric	
fresh_snow_1h:cm	numeric	
fresh_snow_24h:cm	numeric	
fresh_snow_3h:cm	numeric	
fresh_snow_6h:cm	numeric	
hour	numeric	
is_day:idx	category	
is_in_shadow:idx	category	

location	category
month	category
msl_pressure:hPa	numeric
precip_5min:mm	numeric
precip_type_5min:idx	category
pressure_100m:hPa	numeric
pressure_50m:hPa	numeric
prob_rime:p	numeric
rain_water:kgm2	category
relative_humidity_1000hPa:p	numeric
sfc_pressure:hPa	numeric
snow_depth:cm	numeric
snow_melt_10min:mm	category
snow_water:kgm2	numeric
sun_azimuth:d	numeric
sun_elevation:d	numeric
super_cooled_liquid_water:kgm2	category
t_1000hPa:K	numeric
total_cloud_cover:p	numeric
visibility:m	numeric
weekday	category
wind_speed_10m:ms	numeric
wind_speed_u_10m:ms	numeric
wind_speed_v_10m:ms	numeric
wind_speed_w_1000hPa:ms	category
y	numeric
year	category

test_data dataset summary

	count	unique	top	freq	mean	\
absolute_humidity_2m:gm3	2160	106			8.206482	
air_density_2m:kgm3	2160	153			1.232807	
ceiling_height_agl:m	1473	1391			2938.389648	
clear_sky_energy_1h:J	2160	1807			1227746.75	
clear_sky_rad:W	2160	1044			341.056641	
cloud_base_agl:m	1879	1771			1797.160156	
dew_or_rime:idx	2160	3			0.040741	
dew_point_2m:K	2160	202			280.783203	
diffuse_rad:W	2160	985			84.915688	
diffuse_rad_1h:J	2160	1806			305696.5	
direct_rad:W	2160	916			114.279816	
direct_rad_1h:J	2160	1634			411408.875	
effective_cloud_cover:p	2160	590			64.113792	
elevation:m	2160	3			12.333333	
estimated_diff_hours	2160	24			27.5	
fresh_snow_12h:cm	2160	2			0.000185	
fresh_snow_1h:cm	2160	2			0.000185	
fresh_snow_24h:cm	2160	2			0.000185	

fresh_snow_3h:cm	2160	2			0.000185
fresh_snow_6h:cm	2160	2			0.000185
hour	2160	24			11.5
is_day:idx	2160	2			0.795833
is_in_shadow:idx	2160	2			0.24537
location	2160	3	A	720	
month	2160	3			5.666667
msl_pressure:hPa	2160	321			1016.805786
precip_5min:mm	2160	27			0.00775
precip_type_5min:idx	2160	3			0.065741
pressure_100m:hPa	2160	359			1002.970825
pressure_50m:hPa	2160	356			1009.007202
prob_rime:p	2160	3			0.01588
rain_water:kgm2	2160	8			0.013056
relative_humidity_1000hPa:p	2160	538			70.920792
sfc_pressure:hPa	2160	363			1015.070374
snow_depth:cm	2160	1			0.0
snow_melt_10min:mm	2160	1			0.0
snow_water:kgm2	2160	16			0.060972
sun_azimuth:d	2160	1830			183.166199
sun_elevation:d	2160	1623			20.292332
super_cooled_liquid_water:kgm2	2160	7			0.065463
t_1000hPa:K	2160	254			284.737732
total_cloud_cover:p	2160	553			69.298981
visibility:m	2160	2155			33304.636719
weekday	2160	7			3.233333
wind_speed_10m:ms	2160	83			2.946759
wind_speed_u_10m:ms	2160	123			1.650694
wind_speed_v_10m:ms	2160	80			-0.187176
wind_speed_w_1000hPa:ms	2160	2			0.000324
year	2160	1			2023.0

	std	min	25%	\
absolute_humidity_2m:gm3	2.201396	3.2	6.6	
air_density_2m:kgm3	0.032116	1.142	1.209	
ceiling_height_agl:m	2913.641113	30.6	891.799988	
clear_sky_energy_1h:J	1104468.625	0.0	64338.124023	
clear_sky_rad:W	307.729095	0.0	13.65	
cloud_base_agl:m	2046.394409	29.799999	486.899994	
dew_or_rime:idx	0.202365	-1.0	0.0	
dew_point_2m:K	4.378817	268.0	277.899994	
diffuse_rad:W	78.422508	0.0	6.925	
diffuse_rad_1h:J	278146.25	0.0	36756.901367	
direct_rad:W	171.838226	0.0	0.0	
direct_rad_1h:J	611480.125	0.0	86.575001	
effective_cloud_cover:p	37.947498	0.0	30.700001	
elevation:m	8.261587	6.0	6.0	
estimated_diff_hours	6.923789	16.0	21.75	

fresh_snow_12h:cm	0.008607	0.0	0.0
fresh_snow_1h:cm	0.008607	0.0	0.0
fresh_snow_24h:cm	0.008607	0.0	0.0
fresh_snow_3h:cm	0.008607	0.0	0.0
fresh_snow_6h:cm	0.008607	0.0	0.0
hour	6.923789	0.0	5.75
is_day:idx	0.403185	0.0	1.0
is_in_shadow:idx	0.430406	0.0	0.0
location			
month	0.596423	5.0	5.0
msl_pressure:hPa	9.728754	986.099976	1011.5
precip_5min:mm	0.033776	0.0	0.0
precip_type_5min:idx	0.249747	0.0	0.0
pressure_100m:hPa	9.644145	971.799988	997.799988
pressure_50m:hPa	9.74076	977.700012	1003.799988
prob_rime:p	0.551282	0.0	0.0
rain_water:kgm2	0.055256	0.0	0.0
relative_humidity_1000hPa:p	15.725973	23.9	60.275
sfc_pressure:hPa	9.840412	983.5	1009.799988
snow_depth:cm	0.0	0.0	0.0
snow_melt_10min:mm	0.0	-0.0	-0.0
snow_water:kgm2	0.219562	0.0	0.0
sun_azimuth:d	109.193207	8.27	85.359253
sun_elevation:d	18.681047	-11.617	1.96475
super_cooled_liquid_water:kgm2	0.115824	0.0	0.0
t_1000hPa:K	5.839595	273.700012	279.799988
total_cloud_cover:p	38.41222	0.0	32.799999
visibility:m	15624.633789	874.400024	19635.100098
weekday	2.186573	0.0	1.0
wind_speed_10m:ms	1.733865	0.0	1.5
wind_speed_u_10m:ms	2.578466	-4.3	-0.2
wind_speed_v_10m:ms	1.50826	-4.4	-1.3
wind_speed_w_1000hPa:ms	0.005685	-0.0	0.0
year	0.0	2023.0	2023.0

	50%	75%	max \
absolute_humidity_2m:gm3	8.0	10.0	14.2
air_density_2m:kgm3	1.238	1.26	1.301
ceiling_height_agl:m	1553.900024	4021.300049	11468.0
clear_sky_energy_1h:J	1056303.125	2372037.5	3005707.0
clear_sky_rad:W	273.849991	646.874985	835.099976
cloud_base_agl:m	997.799988	2298.300049	11467.799805
dew_or_rime:idx	0.0	0.0	1.0
dew_point_2m:K	281.0	284.299988	290.200012
diffuse_rad:W	73.700001	135.600006	312.600006
diffuse_rad_1h:J	272526.046875	488256.03125	1086246.25
direct_rad:W	16.200001	180.399994	668.0
direct_rad_1h:J	60416.199219	686746.859375	2403444.25

effective_cloud_cover:p	77.75	100.0	100.0
elevation:m	7.0	24.0	24.0
estimated_diff_hours	27.5	33.25	39.0
fresh_snow_12h:cm	0.0	0.0	0.4
fresh_snow_1h:cm	0.0	0.0	0.4
fresh_snow_24h:cm	0.0	0.0	0.4
fresh_snow_3h:cm	0.0	0.0	0.4
fresh_snow_6h:cm	0.0	0.0	0.4
hour	11.5	17.25	23.0
is_day:idx	1.0	1.0	1.0
is_in_shadow:idx	0.0	0.0	1.0
location			
month	6.0	6.0	7.0
msl_pressure:hPa	1020.599976	1023.799988	1029.599976
precip_5min:mm	0.0	0.0	0.34
precip_type_5min:idx	0.0	0.0	2.0
pressure_100m:hPa	1006.25	1010.099976	1016.400024
pressure_50m:hPa	1012.299988	1016.200012	1022.5
prob_rime:p	0.0	0.0	23.0
rain_water:kgm2	0.0	0.0	0.7
relative_humidity_1000hPa:p	73.900002	83.699997	98.900002
sfc_pressure:hPa	1018.299988	1022.299988	1028.699951
snow_depth:cm	0.0	0.0	0.0
snow_melt_10min:mm	0.0	0.0	0.0
snow_water:kgm2	0.0	0.0	3.4
sun_azimuth:d	184.236	279.576248	356.984009
sun_elevation:d	18.54	38.102499	49.902
super_cooled_liquid_water:kgm2	0.0	0.1	0.6
t_1000hPa:K	284.799988	288.299988	302.200012
total_cloud_cover:p	95.300003	100.0	100.0
visibility:m	37623.050781	45378.099609	63863.800781
weekday	3.0	5.0	6.0
wind_speed_10m:ms	2.7	4.0	8.8
wind_speed_u_10m:ms	1.6	3.525	8.8
wind_speed_v_10m:ms	-0.3	0.8	4.0
wind_speed_w_1000hPa:ms	0.0	0.0	0.1
year	2023.0	2023.0	2023.0

	dtypes	missing_count	missing_ratio	raw_type \
absolute_humidity_2m:gm3	float32			float
air_density_2m:kgm3	float32			float
ceiling_height_agl:m	float32	687	0.318056	float
clear_sky_energy_1h:J	float32			float
clear_sky_rad:W	float32			float
cloud_base_agl:m	float32	281	0.130093	float
dew_or_rime:idx	float32			float
dew_point_2m:K	float32			float
diffuse_rad:W	float32			float

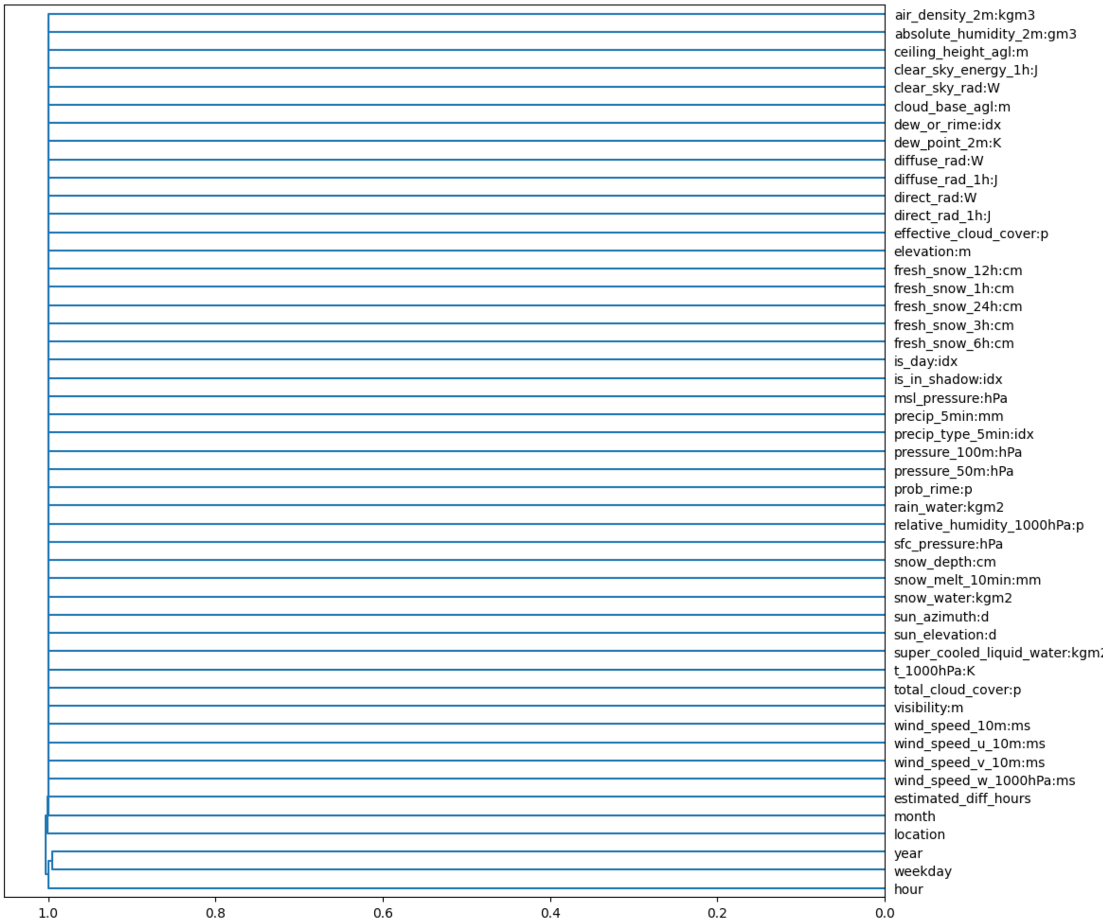
```
diffuse_rad_1h:J                float32                                      float
direct_rad:W                    float32                                      float
direct_rad_1h:J                 float32                                      float
effective_cloud_cover:p         float32                                      float
elevation:m                     float32                                      float
estimated_diff_hours              int64                                        int
fresh_snow_12h:cm               float32                                      float
fresh_snow_1h:cm                float32                                      float
fresh_snow_24h:cm               float32                                      float
fresh_snow_3h:cm                float32                                      float
fresh_snow_6h:cm                float32                                      float
hour                              int64                                        int
is_day:idx                      float32                                      float
is_in_shadow:idx                float32                                      float
location                         object                                     object
month                             int64                                        int
msl_pressure:hPa                float32                                      float
precip_5min:mm                  float32                                      float
precip_type_5min:idx            float32                                      float
pressure_100m:hPa               float32                                      float
pressure_50m:hPa                float32                                      float
prob_rime:p                     float32                                      float
rain_water:kgm2                 float32                                      float
relative_humidity_1000hPa:p     float32                                      float
sfc_pressure:hPa                float32                                      float
snow_depth:cm                   float32                                      float
snow_melt_10min:mm              float32                                      float
snow_water:kgm2                 float32                                      float
sun_azimuth:d                   float32                                      float
sun_elevation:d                 float32                                      float
super_cooled_liquid_water:kgm2  float32                                      float
t_1000hPa:K                     float32                                      float
total_cloud_cover:p             float32                                      float
visibility:m                    float32                                      float
weekday                           int64                                        int
wind_speed_10m:ms               float32                                      float
wind_speed_u_10m:ms             float32                                      float
wind_speed_v_10m:ms             float32                                      float
wind_speed_w_1000hPa:ms         float32                                      float
year                              int64                                        int

                               variable_type special_types
absolute_humidity_2m:gm3             numeric
air_density_2m:kgm3                  numeric
ceiling_height_agl:m                 numeric
clear_sky_energy_1h:J                numeric
clear_sky_rad:W                      numeric
cloud_base_agl:m                     numeric
```

```
dew_or_rime:idx                    category
dew_point_2m:K                      numeric
diffuse_rad:W                       numeric
diffuse_rad_1h:J                    numeric
direct_rad:W                        numeric
direct_rad_1h:J                     numeric
effective_cloud_cover:p             numeric
elevation:m                        category
estimated_diff_hours                numeric
fresh_snow_12h:cm                  category
fresh_snow_1h:cm                   category
fresh_snow_24h:cm                  category
fresh_snow_3h:cm                   category
fresh_snow_6h:cm                   category
hour                                numeric
is_day:idx                         category
is_in_shadow:idx                   category
location                           category
month                              category
msl_pressure:hPa                    numeric
precip_5min:mm                      numeric
precip_type_5min:idx               category
pressure_100m:hPa                   numeric
pressure_50m:hPa                    numeric
prob_rime:p                        category
rain_water:kgm2                    category
relative_humidity_1000hPa:p         numeric
sfc_pressure:hPa                    numeric
snow_depth:cm                      category
snow_melt_10min:mm                 category
snow_water:kgm2                    category
sun_azimuth:d                       numeric
sun_elevation:d                     numeric
super_cooled_liquid_water:kgm2     category
t_1000hPa:K                         numeric
total_cloud_cover:p                 numeric
visibility:m                        numeric
weekday                            category
wind_speed_10m:ms                   numeric
wind_speed_u_10m:ms                 numeric
wind_speed_v_10m:ms                 numeric
wind_speed_w_1000hPa:ms            category
year                               category
```

Types warnings summary

```
                     train_data test_data warnings
estimated_diff_hours      float       int  warning
y                         float        --  warning
```

1.0.1 Feature Distance

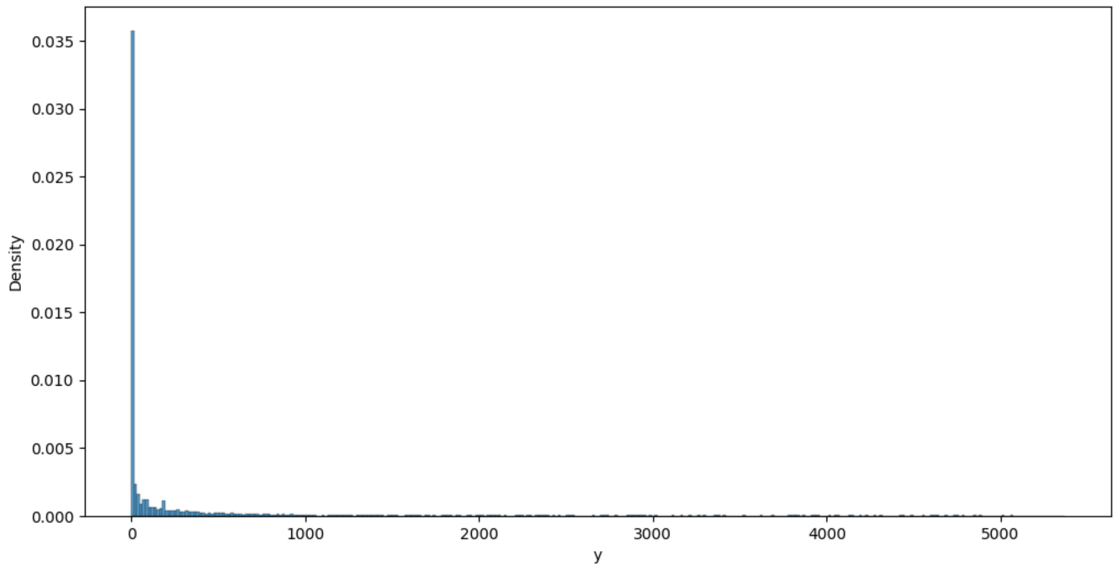



```
[4]: auto.target_analysis(train_data=X_train, label="y")
```

1.1 Target variable analysis

	count	mean	std	min	25%	50%	75%	max	dtypes
y	10000	295.26029	787.46272	-0.0	0.0	0.0	176.4	5365.36	float64

	unique	missing_count	missing_ratio	raw_type	special_types
y	2539			float	

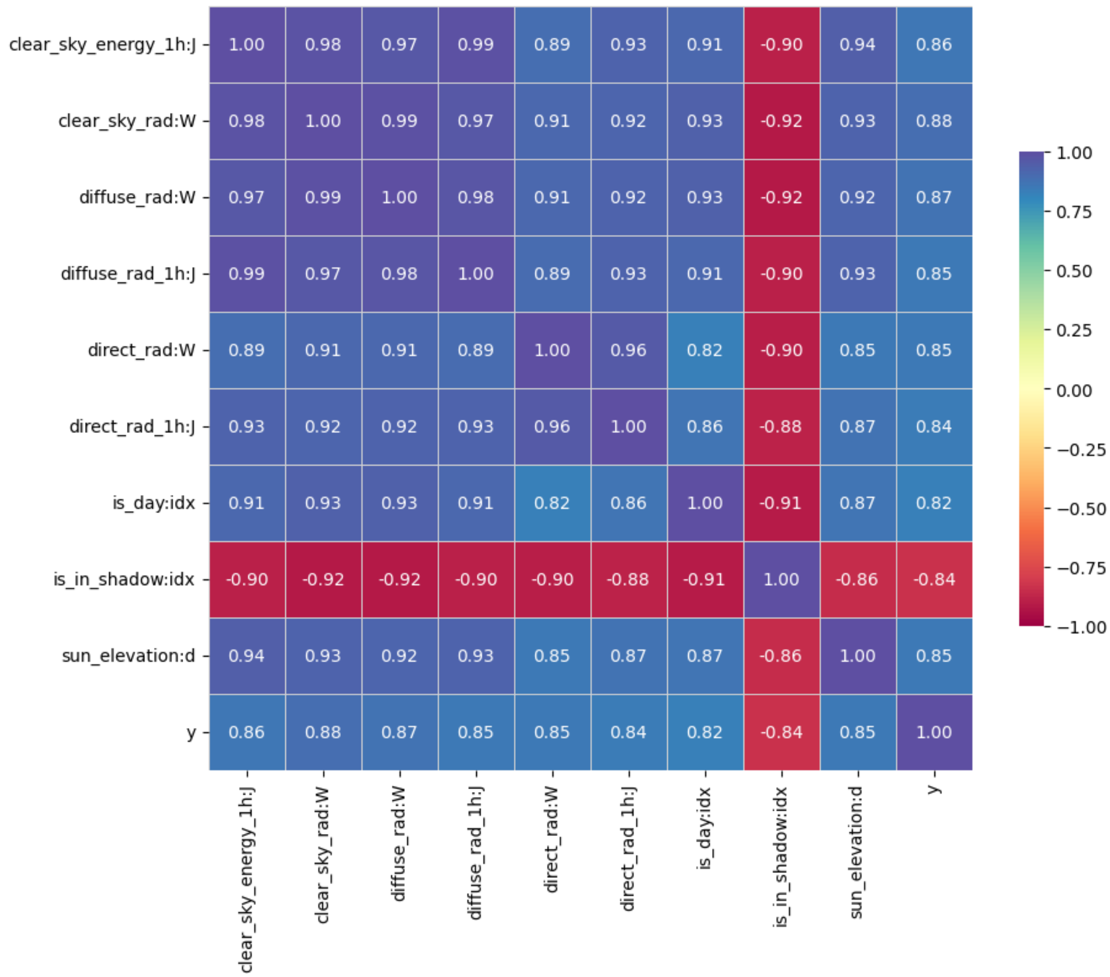


1.1.1 Distribution fits for target variable

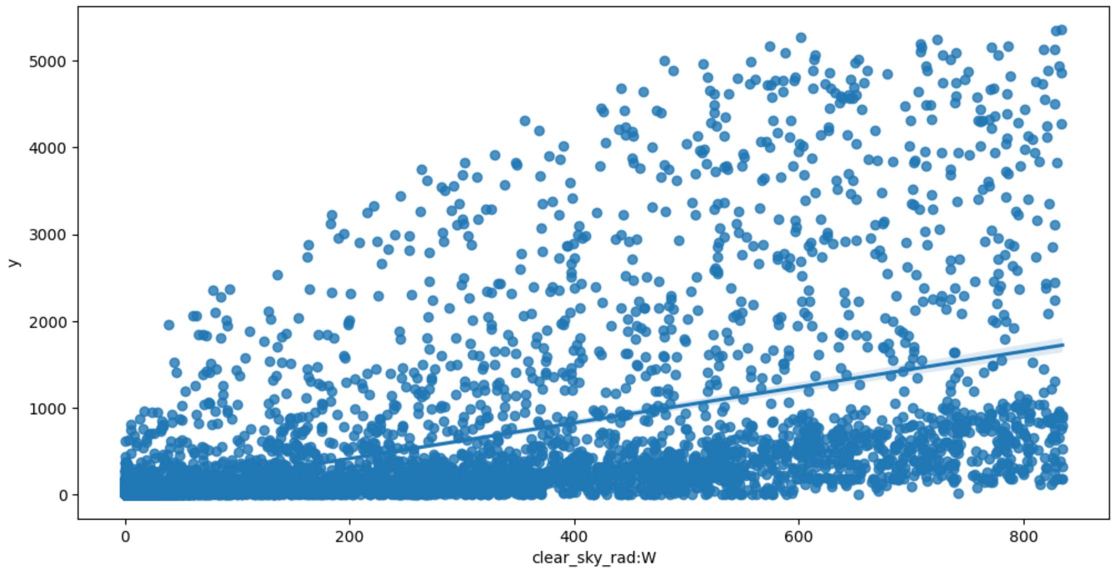
- none of the attempted distribution fits satisfy specified minimum p-value threshold: `0.01`

1.1.2 Target variable correlations

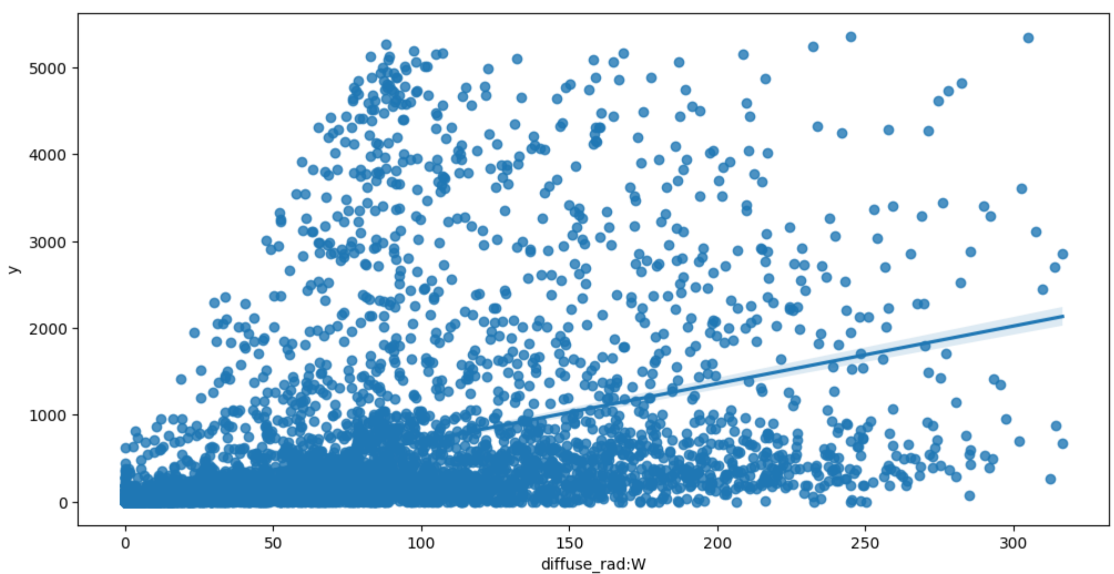
`train_data` - `spearman` correlation matrix; focus: absolute correlation for `y` >= `0.5` (sample size: 10000)



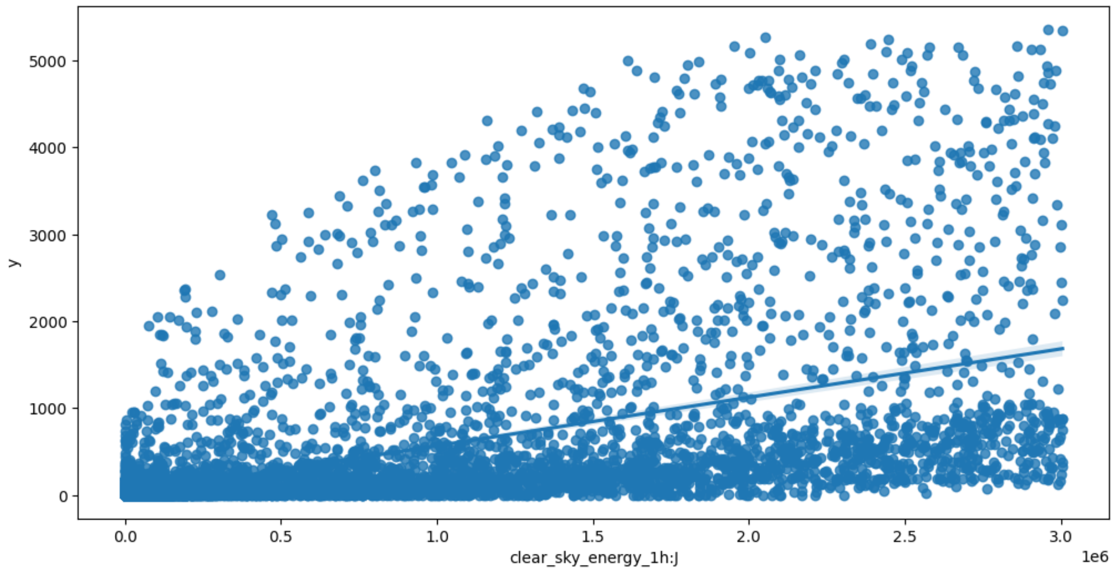
Feature interaction between `clear_sky_rad:W`/`y` in `train_data` (sample size: 10000)



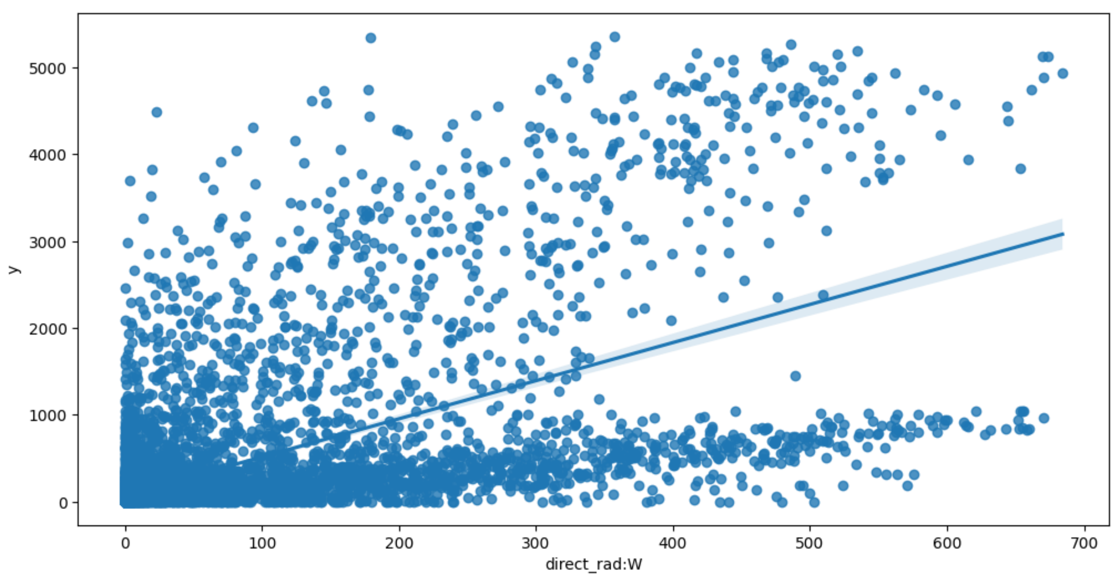
Feature interaction between `diffuse_rad:W/y` in `train_data` (sample size: 10000)



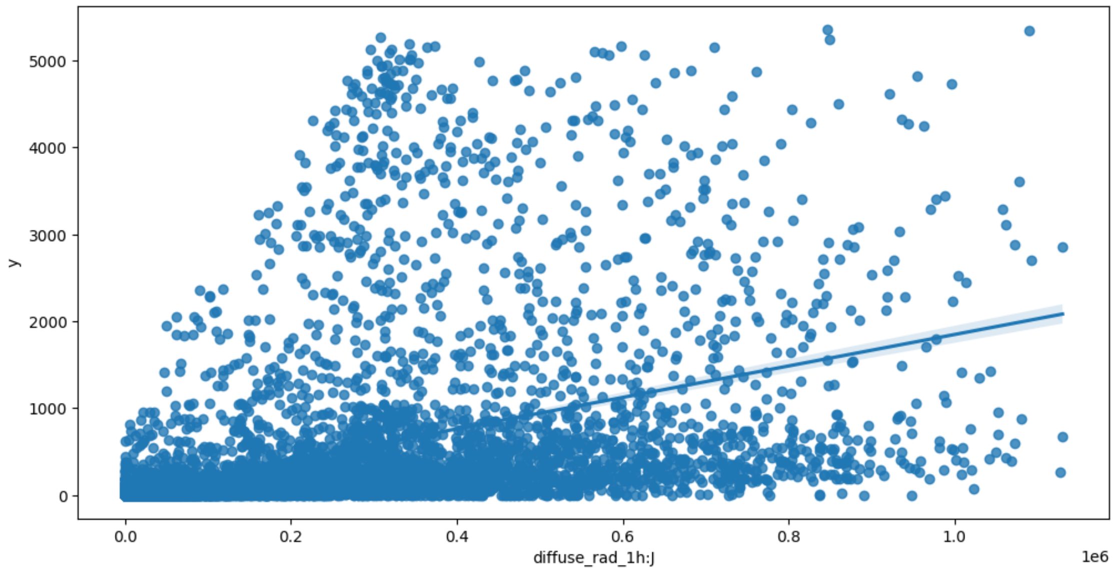
Feature interaction between `clear_sky_energy_1h:J/y` in `train_data` (sample size: 10000)



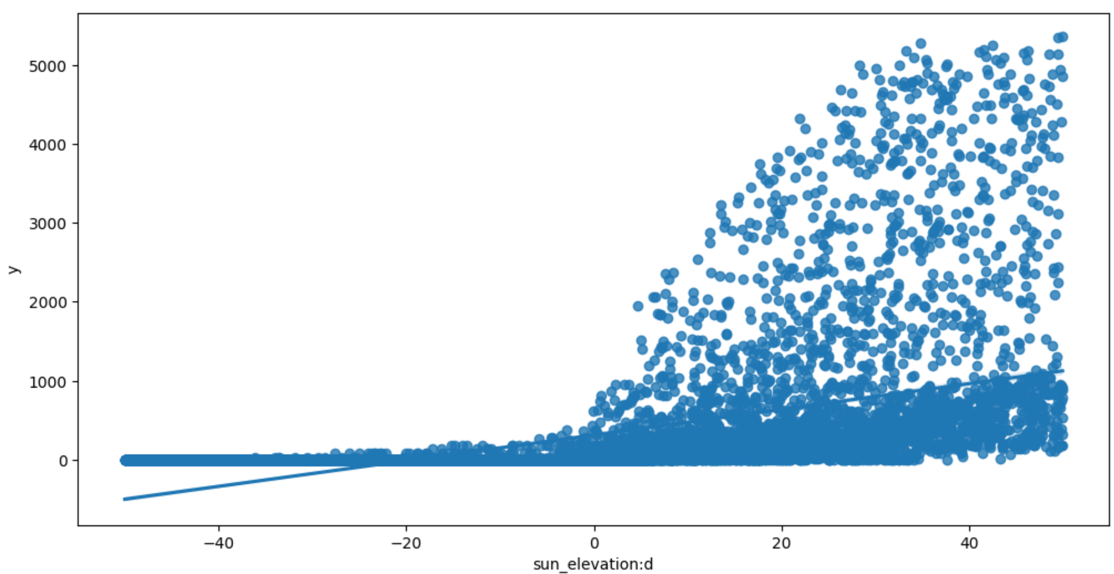
Feature interaction between `direct_rad:W/y` in `train_data` (sample size: 10000)



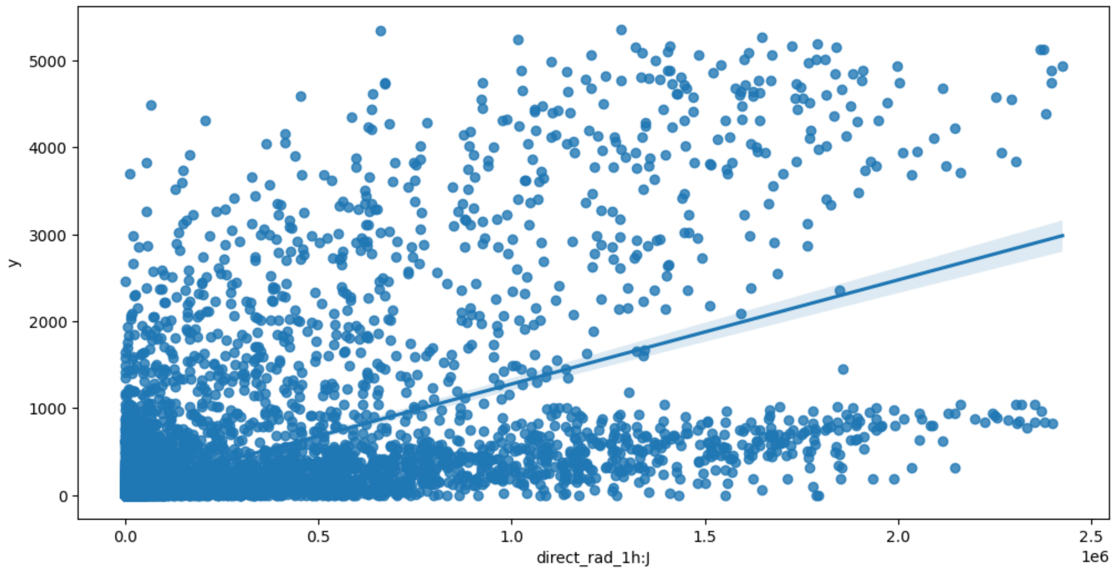
Feature interaction between `diffuse_rad_1h:J/y` in `train_data` (sample size: 10000)



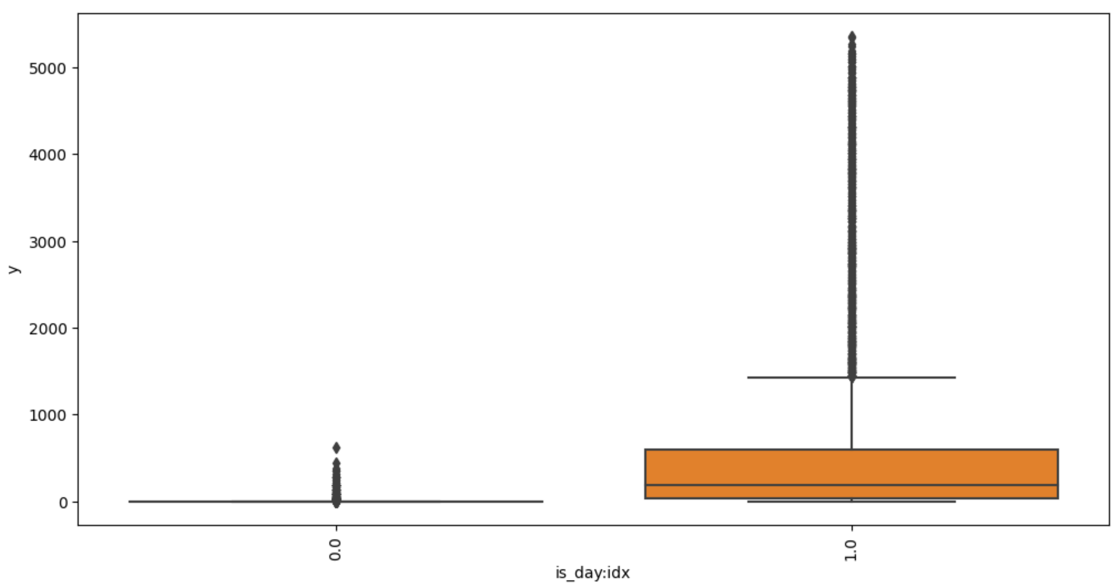
Feature interaction between `sun_elevation:d`/`y` in `train_data` (sample size: 10000)



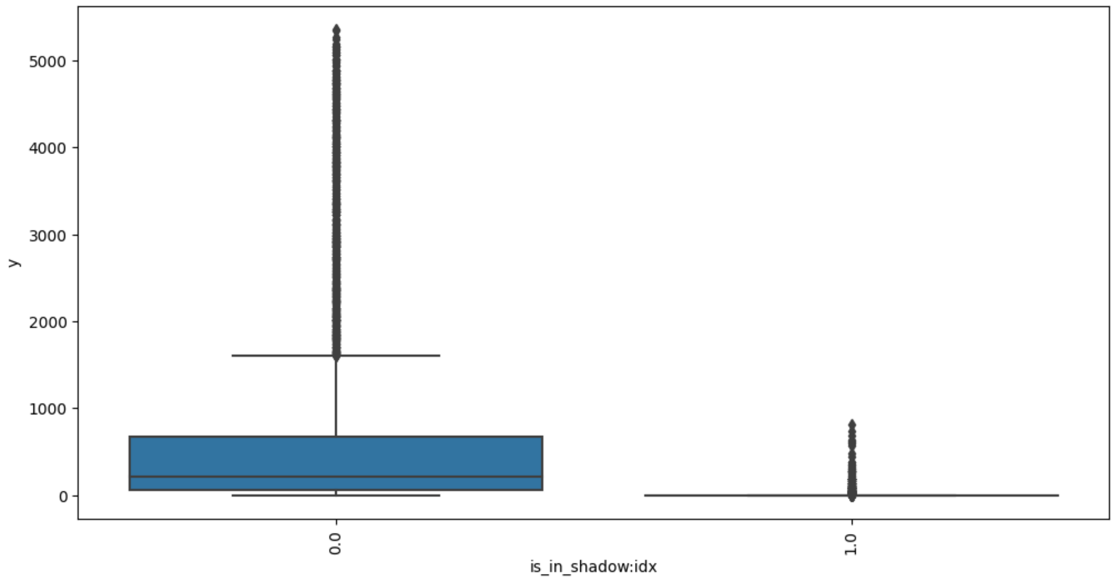
Feature interaction between `direct_rad_1h:J`/`y` in `train_data` (sample size: 10000)



Feature interaction between `is_day:idx`/y in `train_data` (sample size: 10000)



Feature interaction between `is_in_shadow:idx`/y in `train_data` (sample size: 10000)



2 Starting

[5]:
```
import os


# Get the last submission number
last_submission_number = int(max([int(filename.split('_')[1].split('.')[0]) for␣
↪filename in os.listdir('submissions') if "submission" in filename]))
print("Last submission number:", last_submission_number)
print("Now creating submission number:", last_submission_number + 1)

# Create the new filename
new_filename = f'submission_{last_submission_number + 1}'

hello = os.environ.get('HELLO')
if hello is not None:
    new_filename += f'_{hello}'

print("New filename:", new_filename)
```

```
Last submission number: 80
Now creating submission number: 81
New filename: submission_81_jorge
```

[6]:
```
from autogluon.tabular import TabularDataset, TabularPredictor
train_data = TabularDataset('X_train_raw.csv')
train_data.drop(columns=['ds'], inplace=True)
```

```
label = 'y'
metric = 'mean_absolute_error'
time_limit = 60
presets = 'best_quality'
```

[7]:
```
predictors = [None, None, None]
```

[8]:
```
loc = "A"
print(f"Training model for location {loc}...")
predictor = TabularPredictor(label=label, eval_metric=metric,␣
 ↪path=f"AutogluonModels/{new_filename}_{loc}").
 ↪fit(train_data[train_data["location"] == loc], time_limit=time_limit,␣
 ↪presets=presets)
predictors[0] = predictor
```

```
Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=1, num_bag_folds=8,
num_bag_sets=20
Beginning AutoGluon training … Time limit = 60s
AutoGluon will save models to "AutogluonModels/submission_81_jorge_A/"
AutoGluon Version:  0.8.1
Python Version:     3.10.12
Operating System:   Darwin
Platform Machine:   arm64
Platform Version:   Darwin Kernel Version 22.1.0: Sun Oct  9 20:15:09 PDT 2022;
root:xnu-8792.41.9~2/RELEASE_ARM64_T6000
Disk Space Avail:   30.19 GB / 494.38 GB (6.1%)
Train Data Rows:    34085
Train Data Columns: 49
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).
        Label info (max, min, mean, stddev): (5733.42, 0.0, 630.59471,
1165.90242)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    4929.97 MB
        Train Data (Original)  Memory Usage: 15.07 MB (0.3% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 1 features to boolean dtype as they
```

```
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 1): ['location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 44 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])   :  4 | ['hour', 'weekday', 'month', 'year']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 43 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])       :  4 | ['hour', 'weekday', 'month', 'year']
                ('int', ['bool']) :  1 | ['elevation:m']
        0.1s = Fit runtime
        48 features in original data used to generate 48 features in processed
data.
        Train Data (Processed) Memory Usage: 12.85 MB (0.3% of available memory)
Data preprocessing and feature engineering runtime = 0.13s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
```

```
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
AutoGluon will fit 2 stack levels (L1 to L2) …
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 39.91s of the
59.87s of remaining time.

Training model for location A…

        Not enough time to generate out-of-fold predictions for model. Estimated
time required was 170.91s compared to 51.85s of available time.
        Time limit exceeded… Skipping KNeighborsUnif_BAG_L1.
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 37.36s of the
57.32s of remaining time.
        Not enough time to generate out-of-fold predictions for model. Estimated
time required was 205.93s compared to 48.54s of available time.
        Time limit exceeded… Skipping KNeighborsDist_BAG_L1.
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 34.29s of the
54.26s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -161.5377        = Validation score   (-mean_absolute_error)
        27.12s   = Training   runtime
        61.97s   = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 59.87s of the
13.14s of remaining time.
        -161.5377        = Validation score   (-mean_absolute_error)
        0.01s    = Training   runtime
        0.0s     = Validation runtime
Fitting 9 L2 models …
Fitting model: LightGBMXT_BAG_L2 … Training model for up to 13.13s of the
13.12s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -163.4182        = Validation score   (-mean_absolute_error)
        2.35s    = Training   runtime
        0.53s    = Validation runtime
Fitting model: LightGBM_BAG_L2 … Training model for up to 8.54s of the 8.53s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
```

```
        -161.3785        = Validation score   (-mean_absolute_error)
        1.81s    = Training   runtime
        0.16s    = Validation runtime
Fitting model: RandomForestMSE_BAG_L2 … Training model for up to 4.8s of the
4.8s of remaining time.
        -160.8174        = Validation score   (-mean_absolute_error)
        24.86s   = Training   runtime
        0.86s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L3 … Training model for up to 59.87s of the
-21.27s of remaining time.
        -159.4455        = Validation score   (-mean_absolute_error)
        0.16s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 81.45s … Best model:
"WeightedEnsemble_L3"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_81_jorge_A/")
```

[9]:
```
loc = "B"
print(f"Training model for location {loc}...")
predictor = TabularPredictor(label=label, eval_metric=metric,␣
 ↪path=f"AutogluonModels/{new_filename}_{loc}").
 ↪fit(train_data[train_data["location"] == loc], time_limit=time_limit,␣
 ↪presets=presets)
predictors[1] = predictor
```

```
Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=1, num_bag_folds=8,
num_bag_sets=20
Beginning AutoGluon training … Time limit = 60s
AutoGluon will save models to "AutogluonModels/submission_81_jorge_B/"
AutoGluon Version:  0.8.1
Python Version:     3.10.12
Operating System:   Darwin
Platform Machine:   arm64
Platform Version:   Darwin Kernel Version 22.1.0: Sun Oct  9 20:15:09 PDT 2022;
root:xnu-8792.41.9~2/RELEASE_ARM64_T6000
Disk Space Avail:   29.45 GB / 494.38 GB (6.0%)
Train Data Rows:    32844
Train Data Columns: 49
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).
        Label info (max, min, mean, stddev): (1152.3, -0.0, 96.82478, 193.94649)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
```

```
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    4331.9 MB
        Train Data (Original)  Memory Usage: 14.52 MB (0.3% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 1 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 1): ['location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 44 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])   :  4 | ['hour', 'weekday', 'month', 'year']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 43 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])       :  4 | ['hour', 'weekday', 'month', 'year']
                ('int', ['bool']) :  1 | ['elevation:m']
        0.1s = Fit runtime
        48 features in original data used to generate 48 features in processed
data.
        Train Data (Processed) Memory Usage: 12.38 MB (0.3% of available memory)
Data preprocessing and feature engineering runtime = 0.12s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
User-specified model hyperparameters to be fit:
{
```

```
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
AutoGluon will fit 2 stack levels (L1 to L2) …
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 39.91s of the
59.88s of remaining time.

Training model for location B…

        Not enough time to generate out-of-fold predictions for model. Estimated
time required was 195.85s compared to 51.85s of available time.
        Time limit exceeded… Skipping KNeighborsUnif_BAG_L1.
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 36.88s of the
56.85s of remaining time.
        Not enough time to generate out-of-fold predictions for model. Estimated
time required was 220.95s compared to 47.91s of available time.
        Time limit exceeded… Skipping KNeighborsDist_BAG_L1.
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 33.46s of the
53.43s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -25.7449         = Validation score   (-mean_absolute_error)
        28.32s   = Training   runtime
        65.73s   = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 59.88s of the
14.16s of remaining time.
        -25.7449         = Validation score   (-mean_absolute_error)
        0.01s    = Training   runtime
        0.0s     = Validation runtime
Fitting 9 L2 models …
Fitting model: LightGBMXT_BAG_L2 … Training model for up to 14.1s of the
```

```
14.06s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -24.2516         = Validation score   (-mean_absolute_error)
        5.29s    = Training   runtime
        1.3s     = Validation runtime
Fitting model: LightGBM_BAG_L2 … Training model for up to 4.97s of the 4.94s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -23.6458         = Validation score   (-mean_absolute_error)
        1.99s    = Training   runtime
        0.19s    = Validation runtime
Fitting model: RandomForestMSE_BAG_L2 … Training model for up to 0.91s of the
0.89s of remaining time.
        -22.1865         = Validation score   (-mean_absolute_error)
        25.62s   = Training   runtime
        0.85s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L3 … Training model for up to 59.88s of the
-25.95s of remaining time.
        -22.1865         = Validation score   (-mean_absolute_error)
        0.14s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 86.12s … Best model:
"WeightedEnsemble_L3"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_81_jorge_B/")
```

[10]:
```python
loc = "C"
print(f"Training model for location {loc}...")
predictor = TabularPredictor(label=label, eval_metric=metric,␣
 ↪path=f"AutogluonModels/{new_filename}_{loc}").
 ↪fit(train_data[train_data["location"] == loc], time_limit=time_limit,␣
 ↪presets=presets)
predictors[2] = predictor
```

```
Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=1, num_bag_folds=8,
num_bag_sets=20
Beginning AutoGluon training … Time limit = 60s
AutoGluon will save models to "AutogluonModels/submission_81_jorge_C/"
AutoGluon Version:  0.8.1
Python Version:     3.10.12
Operating System:   Darwin
Platform Machine:   arm64
Platform Version:   Darwin Kernel Version 22.1.0: Sun Oct  9 20:15:09 PDT 2022;
root:xnu-8792.41.9~2/RELEASE_ARM64_T6000
```

```
Disk Space Avail:   28.83 GB / 494.38 GB (5.8%)
Train Data Rows:    26095
Train Data Columns: 49
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and label-values can't be converted to int).
        Label info (max, min, mean, stddev): (999.6, -0.0, 77.63106, 165.81688)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    4428.79 MB
        Train Data (Original)  Memory Usage: 11.53 MB (0.3% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 1 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 1): ['location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 44 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])   :  4 | ['hour', 'weekday', 'month', 'year']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 43 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])       :  4 | ['hour', 'weekday', 'month', 'year']
                ('int', ['bool']) :  1 | ['elevation:m']
        0.1s = Fit runtime
        48 features in original data used to generate 48 features in processed
```

```
data.
        Train Data (Processed) Memory Usage: 9.84 MB (0.2% of available memory)
Data preprocessing and feature engineering runtime = 0.13s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
AutoGluon will fit 2 stack levels (L1 to L2) …
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 39.9s of the
59.87s of remaining time.

Training model for location C…

        Not enough time to generate out-of-fold predictions for model. Estimated
time required was 99.89s compared to 51.85s of available time.
        Time limit exceeded… Skipping KNeighborsUnif_BAG_L1.
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 37.94s of the
57.9s of remaining time.
        Not enough time to generate out-of-fold predictions for model. Estimated
time required was 86.14s compared to 49.3s of available time.
        Time limit exceeded… Skipping KNeighborsDist_BAG_L1.
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 36.25s of the
56.21s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -17.0996         = Validation score   (-mean_absolute_error)
```

```
        23.53s   = Training   runtime
        44.64s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 4.44s of the 24.41s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -19.0788         = Validation score   (-mean_absolute_error)
        4.37s    = Training   runtime
        1.22s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 59.87s of the
17.79s of remaining time.
        -17.0784         = Validation score   (-mean_absolute_error)
        0.09s    = Training   runtime
        0.0s     = Validation runtime
Fitting 9 L2 models …
Fitting model: LightGBMXT_BAG_L2 … Training model for up to 17.69s of the
17.68s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -17.7999         = Validation score   (-mean_absolute_error)
        2.08s    = Training   runtime
        0.4s     = Validation runtime
Fitting model: LightGBM_BAG_L2 … Training model for up to 13.48s of the 13.48s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -17.2792         = Validation score   (-mean_absolute_error)
        1.61s    = Training   runtime
        0.12s    = Validation runtime
Fitting model: RandomForestMSE_BAG_L2 … Training model for up to 10.02s of the
10.01s of remaining time.
        -17.0599         = Validation score   (-mean_absolute_error)
        19.24s   = Training   runtime
        0.52s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L3 … Training model for up to 59.87s of the
-9.96s of remaining time.
        -16.9596         = Validation score   (-mean_absolute_error)
        0.14s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 70.12s … Best model:
"WeightedEnsemble_L3"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_81_jorge_C/")
```

3 Submit

[11]:
```python
import pandas as pd
import matplotlib.pyplot as plt

train_data_with_dates = TabularDataset('X_train_raw.csv')
train_data_with_dates["ds"] = pd.to_datetime(train_data_with_dates["ds"])

test_data = TabularDataset('X_test_raw.csv')
test_data["ds"] = pd.to_datetime(test_data["ds"])
#test_data
```

```
Loaded data from: X_train_raw.csv | Columns = 51 / 51 | Rows = 93024 -> 93024
Loaded data from: X_test_raw.csv | Columns = 50 / 50 | Rows = 2160 -> 2160
```

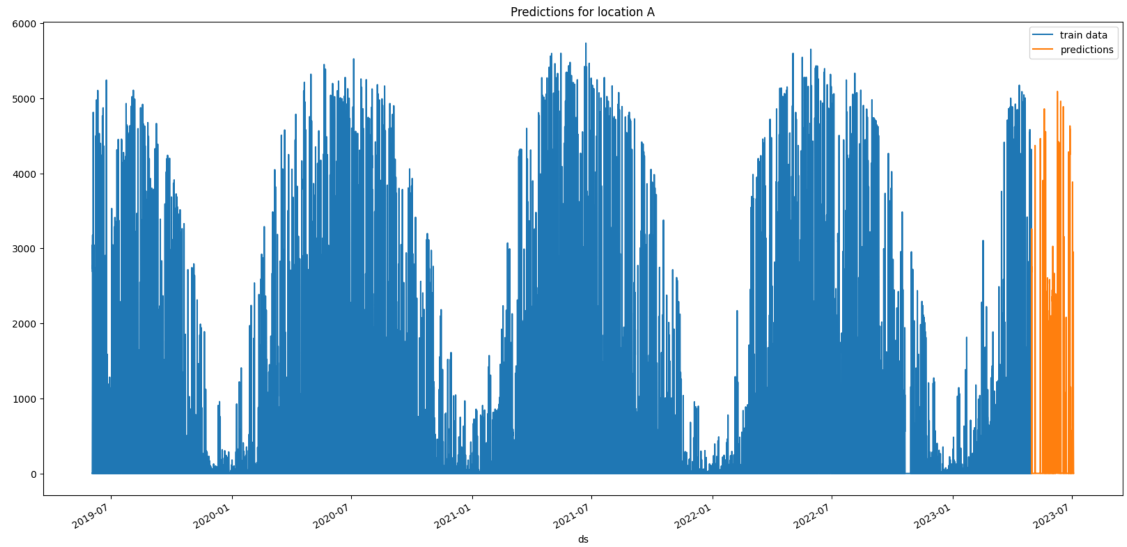
[12]:
```python
test_ids = TabularDataset('test.csv')
test_ids["time"] = pd.to_datetime(test_ids["time"])
# merge test_data with test_ids
test_data_merged = pd.merge(test_data, test_ids, how="inner", right_on=["time",
 ↪"location"], left_on=["ds", "location"])

#test_data_merged
```

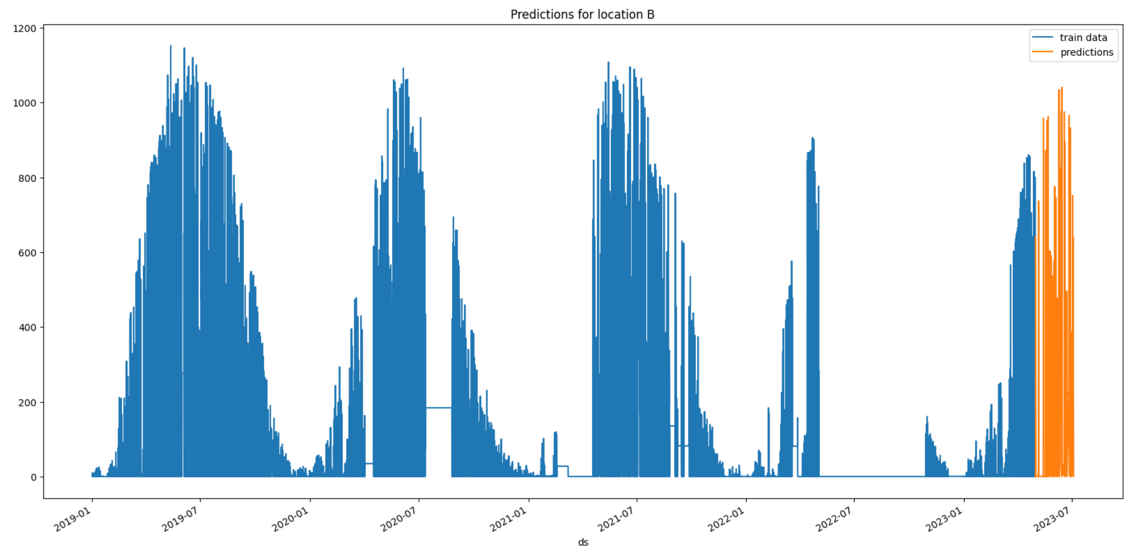
```
Loaded data from: test.csv | Columns = 4 / 4 | Rows = 2160 -> 2160
```

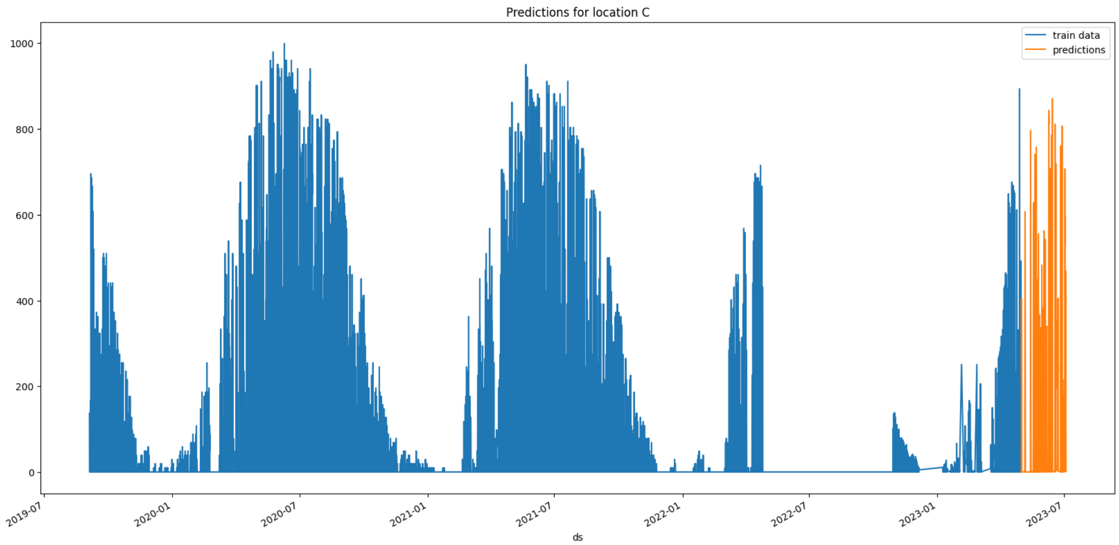
[13]:
```python
# predict, grouped by location
predictions = []
location_map = {
    "A": 0,
    "B": 1,
    "C": 2
}
for loc, group in test_data.groupby('location'):
    i = location_map[loc]
    subset = test_data_merged[test_data_merged["location"] == loc].
 ↪reset_index(drop=True)
    #print(subset)
    pred = predictors[i].predict(subset)
    subset["prediction"] = pred
    predictions.append(subset)
```

[14]:
```python
# plot predictions for location A, in addition to train data for A
for loc, idx in location_map.items():
    fig, ax = plt.subplots(figsize=(20, 10))
    # plot train data
    train_data_with_dates[train_data_with_dates["location"]==loc].plot(x='ds',
 ↪y='y', ax=ax, label="train data")
```

```python
    # plot predictions
    predictions[idx].plot(x='ds', y='prediction', ax=ax, label="predictions")

    # title
    ax.set_title(f"Predictions for location {loc}")
```







[15]:
```
# concatenate predictions
submissions_df = pd.concat(predictions)
submissions_df = submissions_df[["id", "prediction"]]
submissions_df
```

[15]:
```
       id  prediction
0       0    1.474567
1       1    1.537354
2       2    1.680374
3       3   47.797668
4       4  300.030823
..    ...         ...
715  2155   83.732719
716  2156   61.742329
717  2157   29.696980
718  2158    3.763743
719  2159    2.140930

[2160 rows x 2 columns]
```

[16]:
```
# Save the submission DataFrame to submissions folder, create new name based on
 ↪last submission, format is submission_<last_submission_number + 1>.csv

# Save the submission
print(f"Saving submission to submissions/{new_filename}.csv")
submissions_df.to_csv(os.path.join('submissions', f"{new_filename}.csv"),
 ↪index=False)
```

```
Saving submission to submissions/submission_81_jorge.csv
```

[17]:
```python
# save this notebook to submissions folder
import subprocess
import os
subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
↪join('notebook_pdfs', f"{new_filename}.pdf"), "autogluon_each_location.
↪ipynb"])
```

```
[NbConvertApp] Converting notebook autogluon_each_location.ipynb to pdf
[NbConvertApp] Support files will be in notebook_pdfs/submission_81_jorge_files/
[NbConvertApp] Making directory
./notebook_pdfs/submission_81_jorge_files/notebook_pdfs
[NbConvertApp] Writing 121410 bytes to notebook.tex
[NbConvertApp] Building PDF
[NbConvertApp] Running xelatex 3 times: ['xelatex', 'notebook.tex', '-quiet']
[NbConvertApp] Running bibtex 1 time: ['bibtex', 'notebook']
[NbConvertApp] WARNING | bibtex had problems, most likely because there were no
citations
[NbConvertApp] PDF successfully created
[NbConvertApp] Writing 372019 bytes to notebook_pdfs/submission_81_jorge.pdf
```

[17]:
```
CompletedProcess(args=['jupyter', 'nbconvert', '--to', 'pdf', '--output',
'notebook_pdfs/submission_81_jorge.pdf', 'autogluon_each_location.ipynb'],
returncode=0)
```

[23]:
```python
# feature importance
predictors[0].feature_importance(feature_stage="original",␣
↪data=train_data[train_data["location"] == "A"][-24*60*1:])
```

```
These features in provided data are not utilized by the predictor and will be
ignored: ['location']
Computing feature importance via permutation shuffling for 48 features using
1440 rows with 5 shuffle sets…
        639.68s = Expected runtime (127.94s per shuffle set)
```

[ ]:
```python
subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
↪join('notebook_pdfs', f"{new_filename}_with_feature_importance.pdf"),␣
↪"autogluon_each_location.ipynb"])
```

```
[NbConvertApp] Converting notebook autogluon_each_location.ipynb to pdf
[NbConvertApp] Support files will be in notebook_pdfs/submission_78_jorge_files/
[NbConvertApp] Making directory
./notebook_pdfs/submission_78_jorge_files/notebook_pdfs
[NbConvertApp] Writing 76131 bytes to notebook.tex
[NbConvertApp] Building PDF
[NbConvertApp] Running xelatex 3 times: ['xelatex', 'notebook.tex', '-quiet']
[NbConvertApp] Running bibtex 1 time: ['bibtex', 'notebook']
[NbConvertApp] WARNING | bibtex had problems, most likely because there were no
citations
[NbConvertApp] PDF successfully created
```

```
[NbConvertApp] Writing 251165 bytes to notebook_pdfs/submission_78_jorge.pdf
```

[ ]:
```
CompletedProcess(args=['jupyter', 'nbconvert', '--to', 'pdf', '--output',
'notebook_pdfs/submission_78_jorge.pdf', 'autogluon_each_location.ipynb'],
returncode=0)
```